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Cluster Analysis in Loss Development

Dave Clark
Munich Reinsurance America, Inc.

17 October 2018

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Agenda

1. Introduction

2. How to find clusters:

   a) Cluster analysis

   b) Principal Component Analysis (PCA)

   c) Data transformation (curve fitting)

3. Practical considerations and observations

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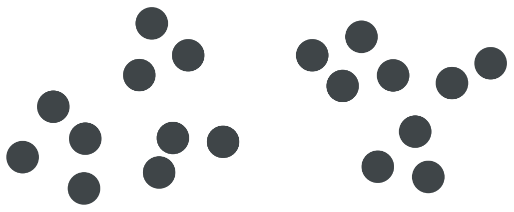
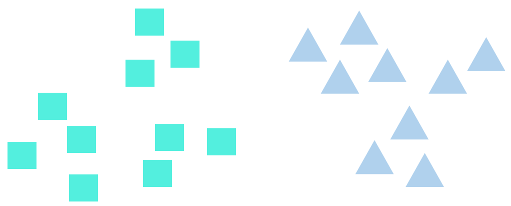
Introduction
Clustering

- Clustering is about finding groups in a set of objects
  - The objects in a group should be similar and groups should be different from each other
  - No need to define the groups in advance (i.e. unsupervised learning)
  - Essential to assess the usefulness and meaning of the identified groups



Original data



Two clusters

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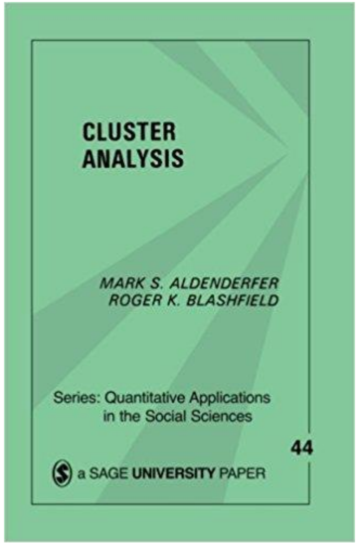
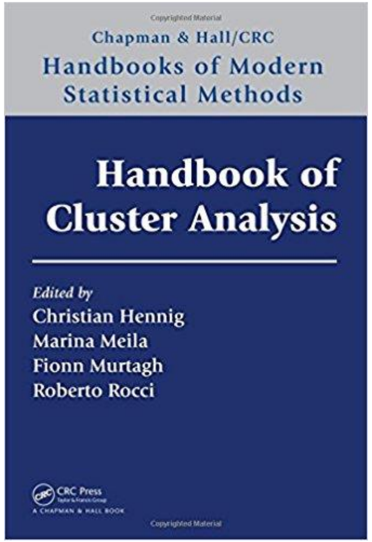
Introduction
Why Clustering?

Cluster Analysis has grown rapidly, especially as computer software has become more readily available.



1984 - 88 pages



2015 - 773 pages

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Introduction
Why Clustering?

- What questions could be answered with cluster analysis?
  - Test the data homogeneity
  - Find a benchmark
  - Identify drivers of development
- What kind of data can be clustered?
  - Segments, contracts or claims
  - County or Region
  - Loss development patterns, loss ratios, severity, frequency…

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Introduction
How to Find Clusters?

- Exploratory Data Analysis

  - Cluster analysis
  - Principal Component Analysis (PCA)
  - Data transformation (curve fitting)

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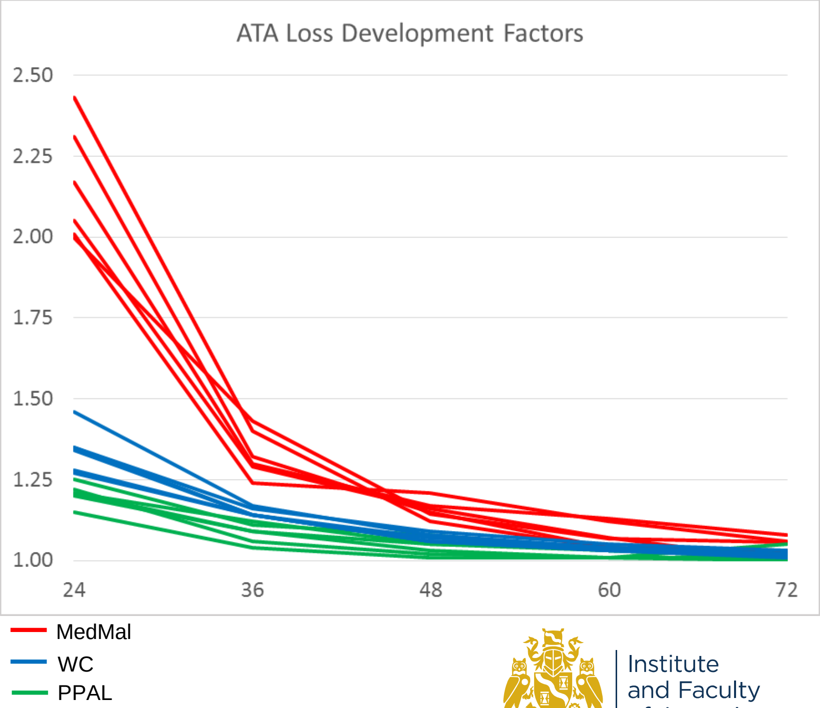
Introduction
Schedule P (Annual Statement) Example

Co.	Line	Ownership	Geographic	Distribution
1	MedMal	Mutual	Regional	Direct, Ind Agency
2	MedMal	Stock	National	Direct, Ind Agency
3	PPAL	Stock	National	MGA, Ind Agency
4	PPAL	Stock	Regional	Ind Agency
5	WC	Stock	National	MGA
6	WC	Mutual	Regional	Ind Agency

…

Co.	24	36	48	60	72
1	2.01	1.24	1.21	1.12	1.06
2	2.05	1.29	1.16	1.07	1.00
3	1.20	1.09	1.05	1.03	1.01
4	1.15	1.04	1.01	1.01	1.00
5	1.34	1.14	1.07	1.04	1.02
6	1.28	1.14	1.06	1.04	1.02

…



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Introduction
Where to Start?

					Explanatory Variables	Variables used for clustering, PCA, …				
Co.	**Line**	**Ownership**	**Geographic**	**Distribution**		**24**	**36**	**48**	**60**	**72**
1	MedMal	Mutual	Regional	Direct, Ind Agency		2.01	1.24	1.21	1.12	1.06
2	MedMal	Stock	National	Direct, Ind Agency		2.05	1.29	1.16	1.07	1.00
3	PPAL	Stock	National	MGA, Ind Agency		1.20	1.09	1.05	1.03	1.01
4	PPAL	Stock	Regional	Ind Agency		1.15	1.04	1.01	1.01	1.00
5	WC	Stock	National	MGA		1.34	1.14	1.07	1.04	1.02
6	WC	Mutual	Regional	Ind Agency		1.28	1.14	1.06	1.04	1.02
			…					…		

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Cluster Analysis
How to Find Clusters?

- Exploratory Data Analysis
  - Cluster analysis
  - Principal Component Analysis (PCA)
  - Data transformation (curve fitting)

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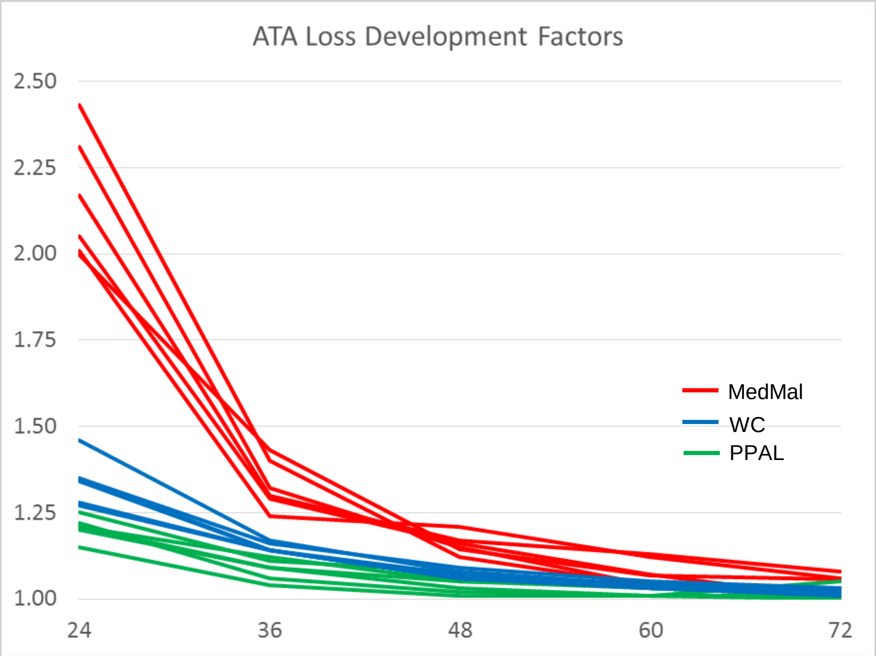
Cluster Analysis
Types of Clustering

- Types of clustering algorithms

  - Hierarchical vs. Partitioned
  - Hard vs. Soft (ex: K-means vs. Fuzzy C-means)
  - Complete vs. Partial
  - Density Based Clusters (ex: DBSCAN)

- **K-means** partitions the data in a user-specified number of clusters (K), in which each observation belongs to the cluster with the nearest mean.

Cluster Analysis
Schedule P example: Cluster Analysis



LOB	K-means 2 clusters	K-means 3 clusters	K-medoids 3 clusters
MedMal	1	1	1
MedMal	1	1	1
MedMal	1	2	1
MedMal	1	1	1
MedMal	1	2	1
MedMal	1	2	1
PPAL	2	3	2
PPAL	2	3	2
PPAL	2	3	2
PPAL	2	3	2
PPAL	2	3	2
PPAL	2	3	2
WC	2	3	3
WC	2	3	3
WC	2	3	3
WC	2	3	3
WC	2	3	3
WC	2	3	3

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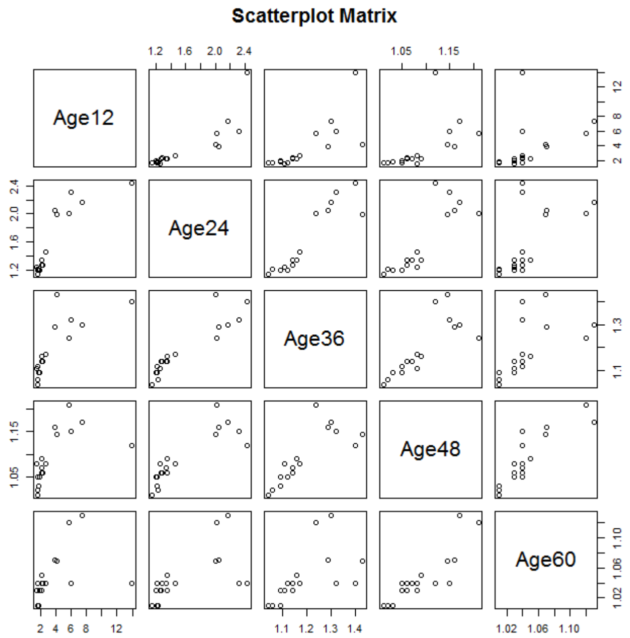
Cluster Analysis
Too Many Dimensions

- Difficulty visualizing more than two dimensions for validation purposes

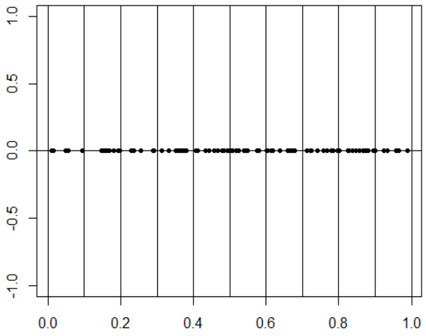
12	24	36	48	60	72
5.70	2.01	1.24	1.21	1.12	1.06
3.86	2.05	1.29	1.16	1.07	1.00
1.92	1.20	1.09	1.05	1.03	1.01
1.64	1.15	1.04	1.01	1.01	1.00
2.19	1.34	1.14	1.07	1.04	1.02
2.33	1.28	1.14	1.06	1.04	1.02
		…			

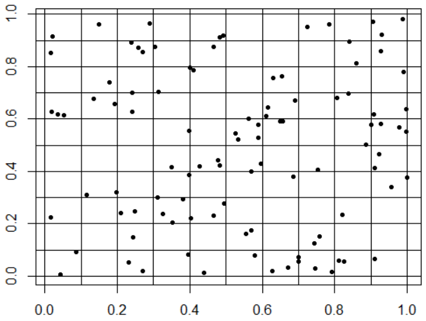


Cluster Analysis
Too Many Dimensions

- Data gets “lost in space”

Randomly generated 100 points in 1D and 2D





- *“In high dimension spaces, distances between points become relatively uniform.”* The performance of clustering algorithms relying on L_1 (sum of absolute values) or L_2 (Euclidian) metrics in high dimensional data may be compromised.

Source: M. Steinbach, L. Ertoz, V. Kumar, “The Challenges of Clustering High Dimensional Data” [7]

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PCA
How to Find Clusters?

- Exploratory Data Analysis
  - Cluster analysis
  - Principal Component Analysis (PCA)
  - Data transformation (curve fitting)

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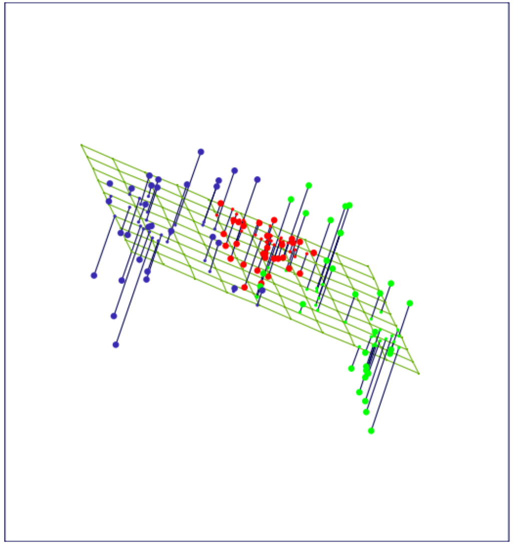
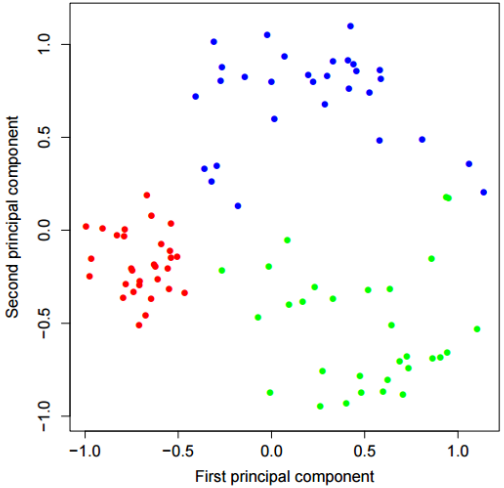
PCA
Principal Component Analysis

- **PCA stretches and rotates data** with the goal to derive the best possible k-dimensional representation of the Euclidean distance among objects.





Source: The Elements of Statistical Learning

PCA
How to perform a PCA?

Data (scaled and centered) → Correlation matrix → Eigenvalues & Eigenvectors

Data (scaled and centered) x Eigenvectors = Principal Components

PCA Interpretation

- PCA provides an opportunity for interpretation
  - PC1 captures the mean loss development
  - PC2 indicates a change in the loss curve shape

Data (scaled and centered) x Eigenvectors = Principal Components

Co	24	36	48	60	72
1	0.99	0.46	2.07	2.18	1.43
2	1.08	0.89	1.17	0.66	-1.04
3	-0.83	-0.82	-0.75	-0.60	-0.78
4	-0.94	-1.30	-1.39	-1.14	-0.96
			…		

x

Dim	1	2
24	0.47	-0.39
36	0.46	-0.38
48	0.49	-0.12
60	0.46	0.36
72	0.34	0.75

=

Co	PC1	PC2
1	3.18	1.04
2	1.45	-1.44
3	-1.67	-0.07
4	-2.57	-0.10
	…	

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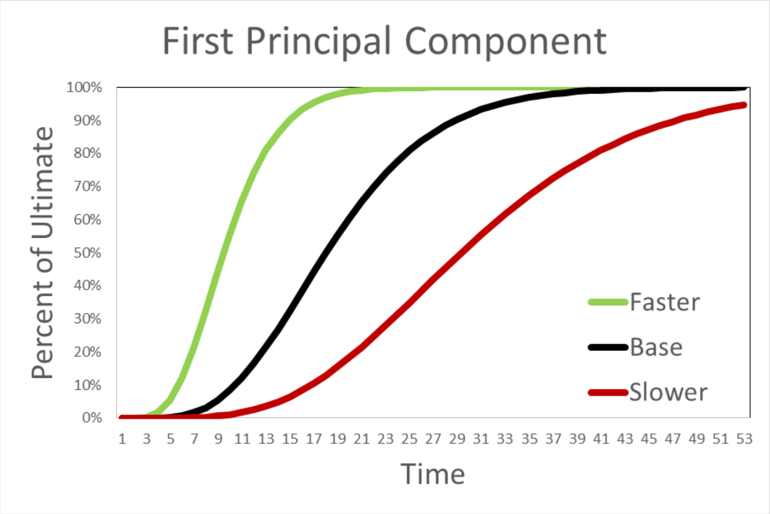
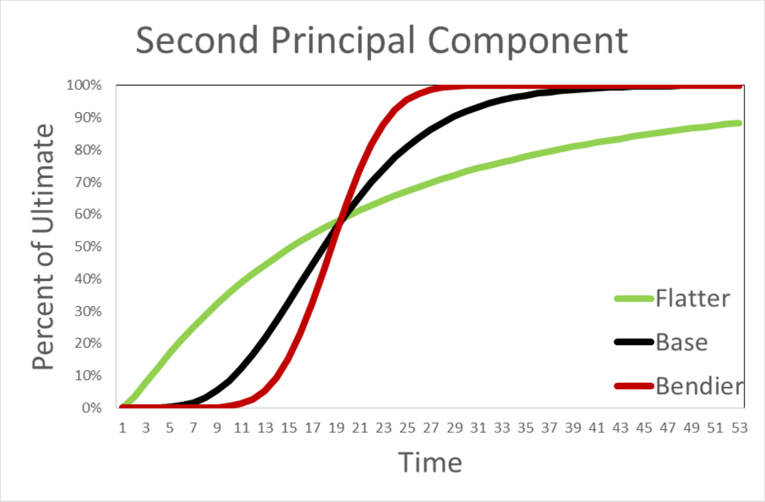
PCA Interpretation





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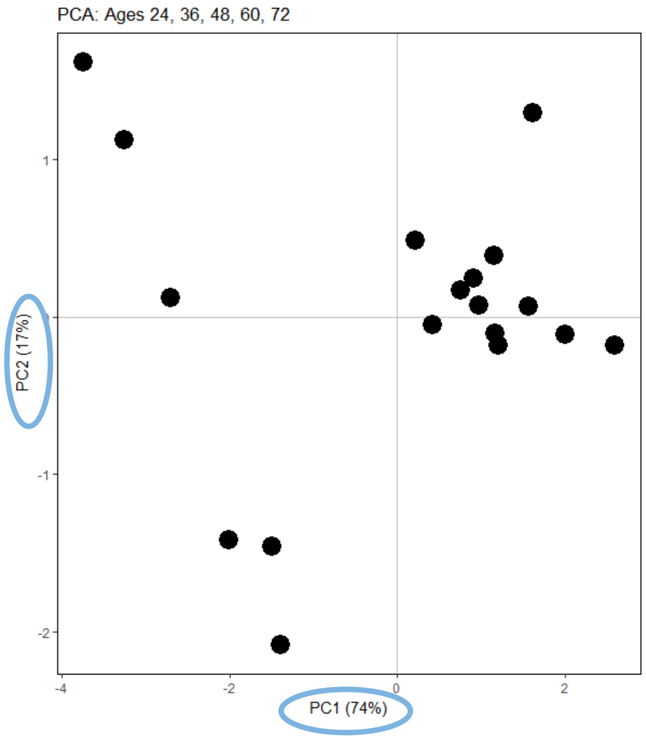
PCA
Schedule P example: Visualization



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PCA
Explanatory Variables

Explanatory Variables

Co.	Line	Ownership	Geographic	Distribution	24	36	48	60	72
1	MedMal	Mutual	Regional	Direct, Ind Agency	2.01	1.24	1.21	1.12	1.06
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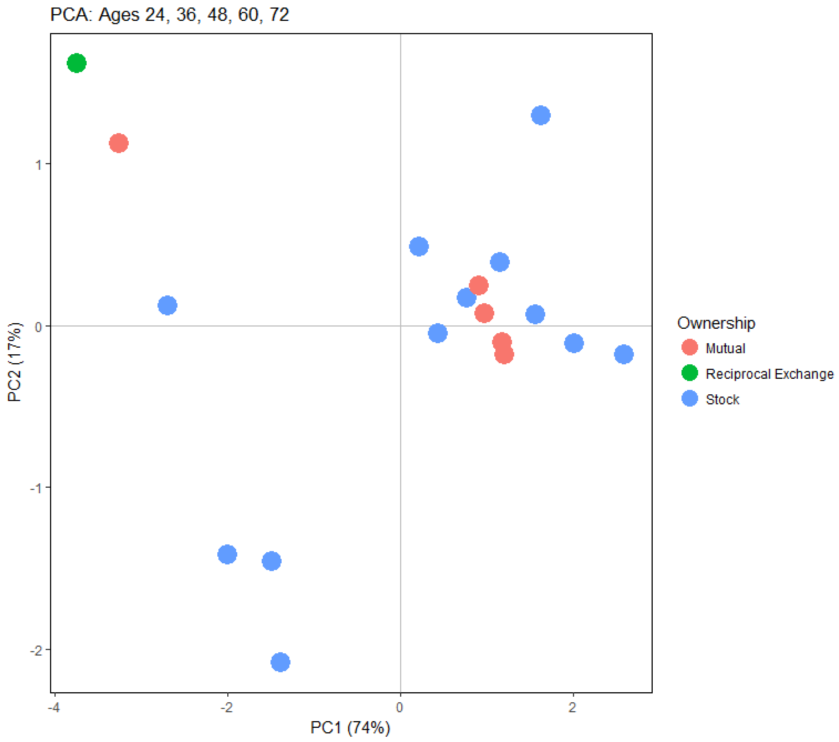
			…				…		

PCA
Schedule P example: Visualization - Ownership



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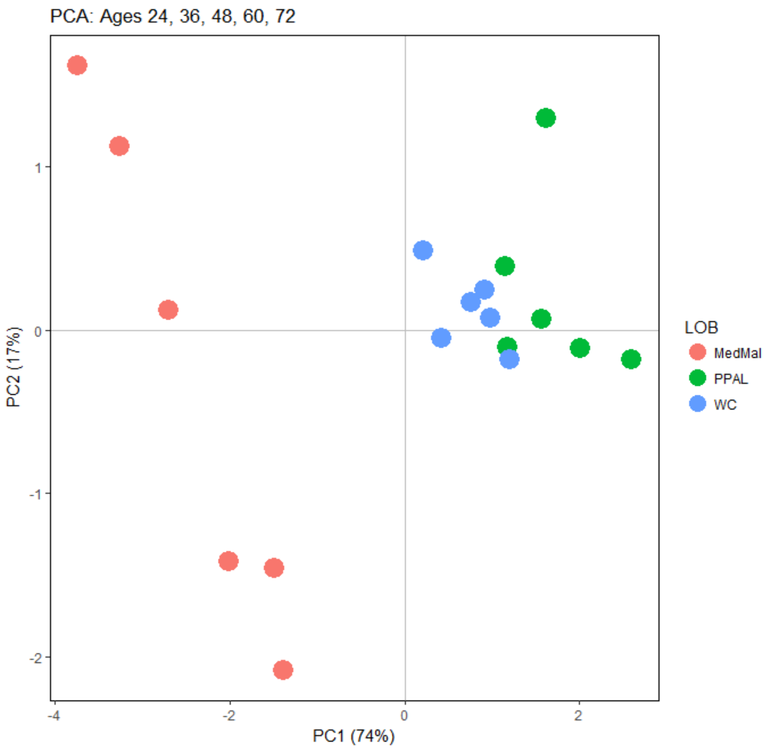
PCA
Schedule P example: Visualization - LOB



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Data Transformation
How to Find Clusters?

- Exploratory Data Analysis
  - Cluster analysis
  - Principal Component Analysis (PCA)
  - Data transformation (curve fitting)

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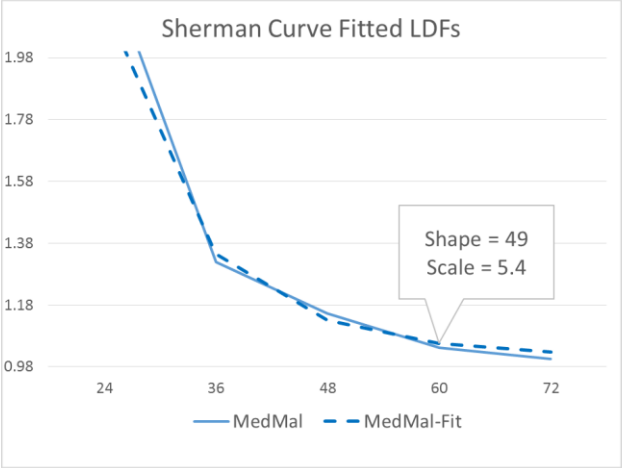
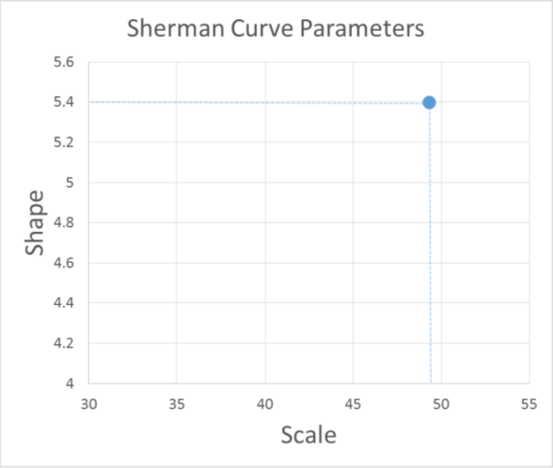
Data Transformation
Sherman Curve

➢ Sherman proposed a curve that fits to the typical LDF pattern

$$ATA_t = 1 + \left(\frac{Scale}{t + c}\right)^{Shape}$$





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Data Transformation
How to estimate the parameters?

- Sherman recommends estimating the parameters by using log-linear regression
  - All actual age-to-age factors must be strictly greater than 1
  - Fitting a logged value rather than actual amounts
- GLM to the rescue!
  - Apply GLM with log-link on actual data

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Data Transformation
Pros & Cons

- Allows comparison of loss development patterns of different sizes
- Does not work well for flat curves
- The focus is on the fit and not on maintaining the distances between points

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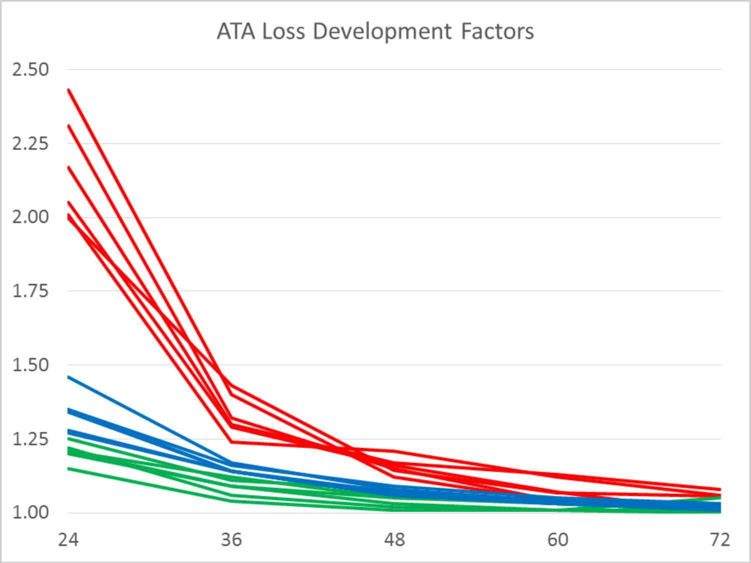
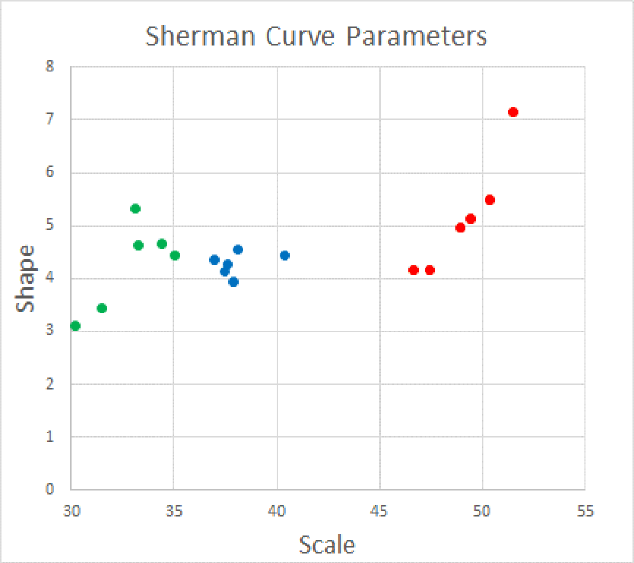
Data Transformation
Schedule P example: Sherman curve





MedMal

WC

PPAL

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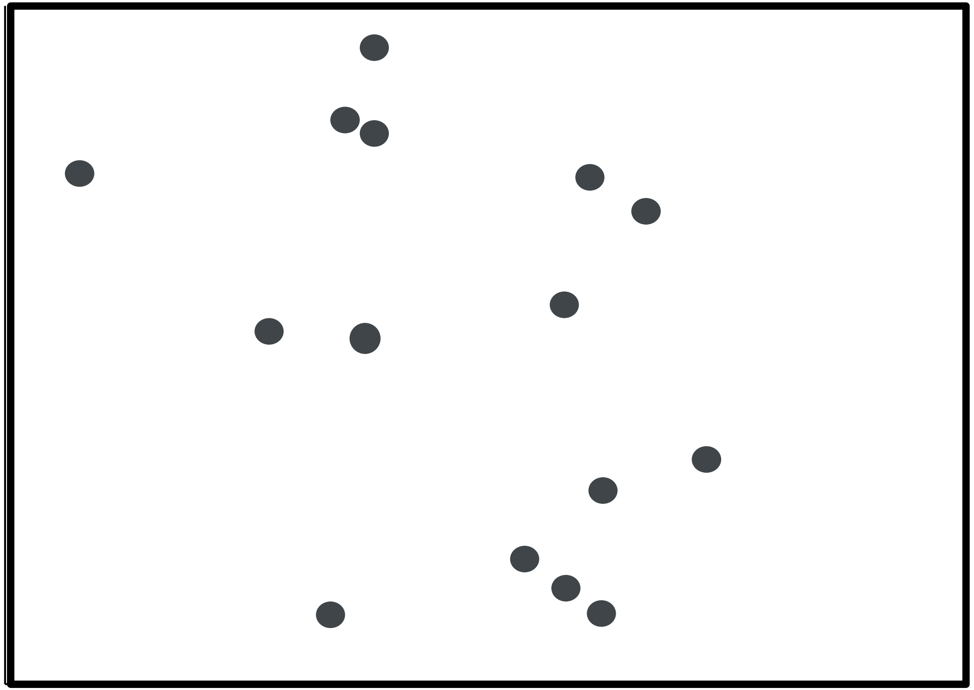
Practical Considerations
How Many Clusters Do You See?



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Practical Considerations
The Coins Experiment

Practical Considerations
Clustering Illusion

“The predisposition to detect patterns and make connections is what leads to discovery and advance. The problem, however, is that this tendency is so strong and so automatic that we sometimes detect patterns when they do not exist.”

T. Gilovich, “How We Know What Isn't So - The Fallibility of Human Reason in Everyday Life”

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Practical Considerations
Correlations between lines of business

- Compare the first principal component for two different lines, written by the same company

- Schedule P data for loss reserving posted on the CAS website
  - 54 companies with CAL and GL lines
  - 20 companies with WC and GL lines
  - Data is from 1988 to 1997

- Check if historical dependency is preserved in more recent years

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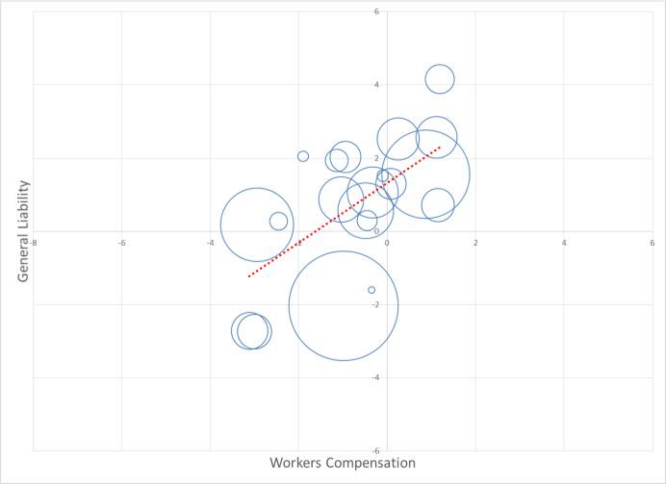
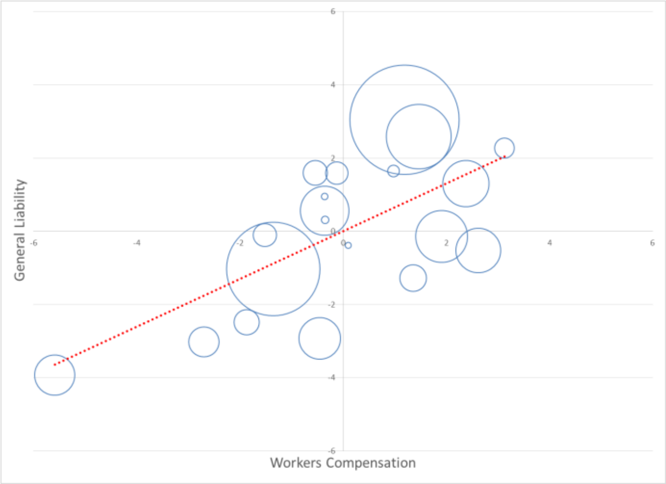
Practical Considerations
First principal component for WC/GL

- PCA on Reported loss

1988 - 1997



1998 - 2007



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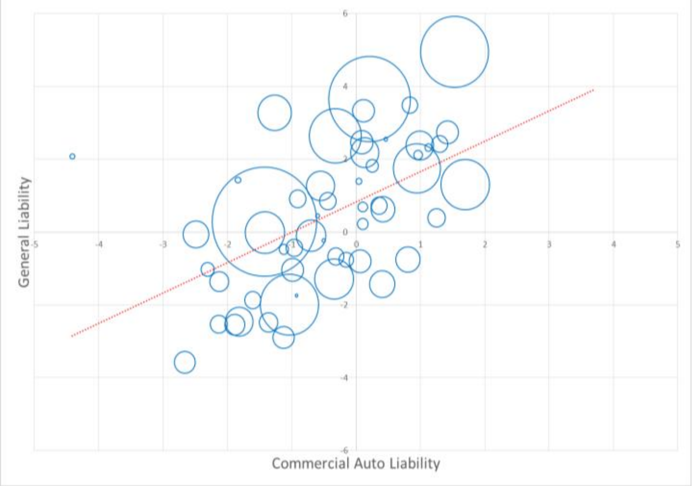
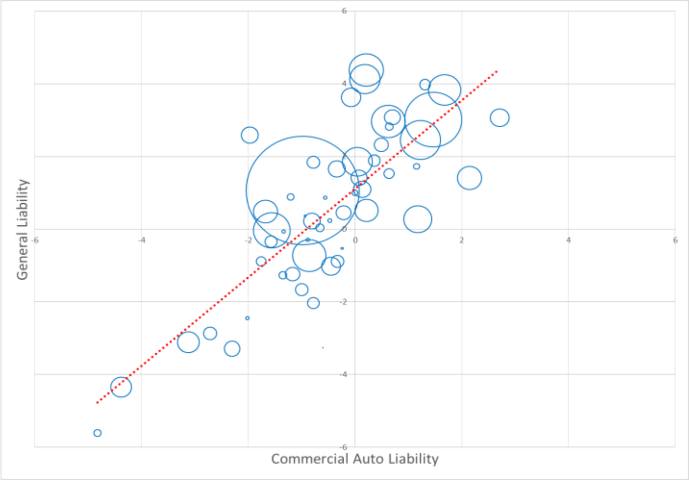
Practical Considerations
First principal component for CAL/GL

- PCA on Reported loss

1988 - 1997



1998 - 2007



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Conclusion
Key Takeaways

- Clustering techniques help us obtain a better understanding of the loss development:
  - Explore the structure of data
  - Go beyond “just” practical grouping of data
  - Identify variables impacting the development
- Each method has strengths and weaknesses
  - Look for robustness between methods

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Selected References

1. D. Clark (2017) **Estimation of Inverse Power Parameters via GLM**, *Actuarial Review, May-June 2017* , https://ar.casact.org/estimation-of-inverse-power-parameters-via-glm/

2. T. Hastie, R. Tibshirani, J. Friedman (2009) **The Elements of Statistical Learning - Data Mining, Inference, and Prediction**, Springer https://web.stanford.edu/~hastie/Papers/ESLII.pdf

3. C. Hennig (2015) **Clustering strategy and method selection,** In C. Hennig, M. Meila, F. Murtagh, and R. Rocci (Eds.). *Handbook of Cluster Analysis*. Chapman and Hall/CRC, http://www.homepages.ucl.ac.uk/~ucakche/

4. C. Hennig, M.Meila, F. Murtagh, R.Rocci (2017) **Handbook of Cluster Analysis,** CRC Press

5. P. Tan, M. Steinbach, V. Kumar (2005) **Cluster Analysis: Basic Concepts and Algorithms,** In P. Tan, M. Steinbach, V. Kumar, *Introduction to Data Mining,* Pearson Addison Wesley, http://www-users.cs.umn.edu/~kumar/dmbook/index.php

6. J. Shlens (2003) **A Tutorial on Principal Component Analysis: Derivation, Discussion and Singular Value Decomposition,** arXiv preprint arXiv:1404.1100, 2014, https://www.cs.princeton.edu/picasso/mats/PCA-Tutorial-Intuition_jp.pdf

7. M. Steinbach, L. Ertoz, V. Kumar, **"The Challenges of Clustering High Dimensional Data"**, https://www-users.cs.umn.edu/~kumar001/papers/high_dim_clustering_19.pdf

8. J. VanderPlas, "**Python Data Science Handbook",** O'Reilly Media, http://shop.oreilly.com/product/0636920034919.do

9. CAS Schedule P data for Loss Reserving: http://www.casact.org/research/index.cfm?fa=loss_reserves_data

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Thank you!

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Risk Solutions

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